

Naive Bayes

* we want to return probabilities and classify using the class with the highest probability

$$\text{Bayes Rule: } P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

naive bayes classifier

$$P(B) = P(B|A)P(A) + P(B|\text{not } A)P(\text{not } A)$$

Naive Bayes Assumption

- to make calculations easier
- assume that X_i and X_j are conditionally independent given Y for all $i \neq j$

$$P(X_1, X_2, \dots, X_d | Y) = \prod_{i=1}^d P(X_i | Y)$$

Conditional Independence

$$P(X|Y, Z) = P(X|Z)$$

Naive Bayes Classifier

$$\begin{aligned} \hat{y} &= \operatorname{argmax}_y P(Y=y | X=x) \quad \rightarrow \text{apply Bayes rule and ignore denominator} \\ &= \operatorname{argmax}_y P(Y=y) P(X=x | Y=y) \\ &= \operatorname{argmax}_y P(Y=y) \prod_{i=1}^d P(X_i=x_i | Y=y) \quad \rightarrow \text{naive bayes assumption} \end{aligned}$$

In naive bayes, we don't have to do optimization for the parameter.

rather, we try different values of y and use the y with the highest probability

Maximum Likelihood Estimation

- given a sample of data, find the parameter that maximize probability of seeing the data
- normally take log, since it is easier to get derivative of logs and exponents become products
- take derivative and set to 0

I observed 5 Heads and 23 Tails. Find θ parameter of Heads probability.

$$\begin{aligned} P_{\theta}(D) &= \theta^5 (1-\theta)^{23} \\ \log(P_{\theta}(D)) &= \log(\theta^5 (1-\theta)^{23}) \\ &= \log(\theta)^5 + \log(1-\theta)^{23} \\ &= 5 \log(\theta) + 23 \log(1-\theta) \\ \log(P_{\theta}(D)) &= 5 \log(\theta) + 23 \log(1-\theta) \\ \frac{\partial}{\partial \theta} [\log(P_{\theta}(D))] &= \frac{\partial}{\partial \theta} [5 \log(\theta) + 23 \log(1-\theta)] = 0 \\ 0 &= \frac{5}{\theta} - \frac{23}{1-\theta} \\ \frac{23}{1-\theta} &= \frac{5}{\theta} \\ 23\theta &= 5 - 5\theta \\ 28\theta &= 5 \\ \theta &= \frac{5}{28} \end{aligned}$$